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Article

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Impacts of seasonal climate variation on rice yield: Evidence from the Central Coast of Vietnam

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ABSTRACT

This study investigates the impact of seasonal climate change on rice productivity in Vietnam's Central Coast, using 26 years of data from 1996 to 2021. To achieve this objective, the study applies a Feasible Generalized Least Squares (FGLS) model to obtain robust estimates for the panel analysis. The findings reveal the consequences of climate variation on rice productivity throughout different seasons. Notably, increases in maximum temperature during the winter–spring season and minimum temperature during the summer–autumn season boost rice yields, while higher maximum temperatures in summer–autumn and minimum temperatures in winter–spring reduce yields. Specifically, a 1% increase in maximum temperature improves winter–spring yields by 1.66% but reduces summer–autumn yields by 1.01%, while a 1% rise in minimum temperature decreases winter–spring yields by 0.30% but enhances summer–autumn yields by 3.32%. In addition, increases in both maximum and minimum relative humidity positively impact yields. The study also finds that a 1% increase in maximum precipitation slightly reduces summer–autumn yields. These findings provide important insights for developing strategies to improve the resilience of rice production to climate change.

IMPACT STATEMENT

This study aims to provide reliable scientific evidence on the impacts of seasonal climate change on rice productivity over an extended period of time in the Central Coast of Vietnam. Its findings can assist policymakers in proposing climate-adaptive farming measures to mitigate adverse effects on rice production and may also serve as a reference for regions with similar climates in other rice-producing countries.

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1. Introduction

Climate change has exerted a significant impact on agriculture worldwide and poses a serious threat to global food security (Malhi et al., 2021; Tilahun, 2021; Emeru, 2022; Mubenga-Tshitaka et al., 2023). The United Nations Framework Convention on Climate Change (UNFCCC) defines climate change as a phenomenon resulting from human activities that alter the composition of the global atmosphere, leading to shifts beyond the natural climate variability observed over comparable periods (WHO, 2016). These changes are monitored through key indicators identified by the Global Climate Observing System (GCOS), including surface temperature, ocean heat content, atmospheric CO₂ levels, and sea levels, Arctic & Antarctic sea ice extent, ocean acidification, and glacier (WMO, 2023). In light of the difficulties in collecting comprehensive climate data, surface temperature is often used to assess the impact of climate change on agriculture. However, climate change is now reconsidered to refer to any alterations in climatic indicators over time, such as temperature or precipitation (Li, 2023). According to NASA (2023), the ten most recent years rank as the warmest on record, and Earth's average temperature in 2023 was approximately 1.36 °C higher than the late 19th century (1850–1900) preindustrial average. This indicates that climate change will continue to be a worrying concern for global agriculture.

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Besides, among various crops, rice is the third-largest cultivated cereal crop worldwide (Bazargan et al., 2014), and it serves as the fundamental food staple for more than half of the world's population, with an annual production of approximately 480 million metric tons of milled rice (Muthayya et al., 2014; Irshad et al., 2018). During the early 1980s, Vietnam transitioned from its status as a food-importing nation to emerging as one of the foremost rice exporters globally within a period of less than two decades (Vu & Nguyen, 2021). By 2023, Vietnam surpassed Thailand to become the second-largest rice exporter globally, with a total volume of 5.9 million tons (USDA, 2023). Rice cultivation in Vietnam plays a pivotal role in enhancing global food security (Shrestha et al., 2016).

However, Vietnam is among the countries that are most vulnerable to the impacts of climate change (Dasgupta et al., 2009; World Bank Group and Asian Development Bank, 2020; Nguyen and Scrimgeour, 2022; Anh et al., 2023). Nguyen et al. (2008) and Anh et al. (2023) indicated that Vietnam's extensive coastline, flanked by high mountains and flat floodplains, exposed over 70% of its population to various natural hazards. Among these regions, the Mekong River Delta, the north-central region, and the central coastal region face heightened vulnerability to the impacts of global warming. Given the challenges posed by climate change, understanding its effects on rice production is vital for devising solutions to enhance current food security and bolster the resilience of agricultural systems. Moreover, because Vietnam has complex seasonal cropping systems, with crop calendars and patterns varying across agro-ecological zones, it is crucial to assess these impacts within the context of specific seasonal variations to effectively investigate the impacts of climate change on rice production (Trinh, 2018). Nevertheless, research on the impact of climate variability on rice production in Vietnam, particularly in the central regions, remains scarce (Chung et al., 2015).

Recent studies have explored the impact of climate change on agricultural production in Vietnam, particularly emphasizing the cultivation of rice, given its significance as one of the world's major rice-producing regions. Despite many studies on the economic impact of climate change in many fields, most of them used cross-sectional data and time series data (Chung et al., 2015; Huynh et al., 2020), and a few used panel data (Trinh, 2018; Nguyen & Scrimgeour, 2022). In addition, most of these studies have utilized Ordinary Least Square, fixed and random effect methods. To the best of our knowledge, there are a limited number of studies in the existing literature that utilize feasible generalized least squares (FGLS) models to examine the impacts of climate change. FGLS models are advantageous in dealing with issues such as group-wise heteroscedasticity and autocorrelation within panels of the stochastic disturbance term. These issues could deviate from the strict assumptions of traditional panel models, potentially leading to biased estimations (Wu et al., 2021). Therefore, applying the model with the strengths outlined above offers a promising approach to resolving existing challenges or issues left unresolved in previous studies in Vietnam. This application is expected to yield reliable results in assessing the impact of climate on rice production in the study area, thereby enhancing the comprehensive understanding and effective management of climate-related risks in the region's agricultural sector.

The objective of this study is to employ a feasible generalized least squares model to examine how climate change, with specific seasonal characteristics, affects rice productivity in the Central Coast of Vietnam from 1996 to 2021. This study makes two main contributions to the existing literature: (i) this study is the first to apply the FGLS model for more in-depth seasonal research of climate change impacts over an extremely extended period of time in the Central Vietnam, while addressing both group-wise heteroscedasticity and autocorrelation to obtain robust estimates for the panel analysis; and (ii) the findings of this study provide scientific evidence for Vietnamese policymakers to propose appropriate farming measures to seasonal climate factors, aimed at adapting to and reducing the adverse impact of climate change on the rice production sector. This scientific evidence can also be referenced for regions with similar climate characteristics in other rice-cultivating countries in the world.

The remainder of this article is organized as follows. [Section 2](#) reviews the literature. [Section 3](#) describes the data sources and the methodology used. [Section 4](#) represents and discusses the results. Finally, [Section 5](#) concludes the study with a summary of the findings and policy implications.

2. Literature review

Researchers are increasingly directing their attention towards the economic consequences of climate change. Previous research has yielded varying results regarding the anticipated response of rice to forthcoming climate change. Rayamajhee et al. (2021) highlighted the vulnerability of rural agricultural households in Nepal to climate change. Employing the stochastic frontier function approach, their findings underscored the significant negative effects on rice production resulting from alterations in both average and extreme precipitation and temperatures. Emphasis was placed on the threats posed by irregular extreme rainfall patterns and a sustained rise in average temperatures. Massagony et al. (2023) applied the feasible generalised least squares (FGLS) model to examine the effects of climate change on rice production in Indonesia using historical data from 1986 to 2016. Their results revealed that increases in temperature and precipitation have adverse effects on rice production, whereas higher relative humidity has a positive impact. Recognizing the adverse impact of temperature changes on rice production, Mukhopadhyay and Das (2023) proposed a proactive solution and found that the adoption of new rice seed varieties with heightened temperature tolerance is more effective in mitigating the challenges posed by climate change.

Numerous studies have examined the impacts of climate change on rice production and yield, spanning diverse scopes (Kontgis et al., 2019), including national (Felkner et al., 2009; Nahar et al., 2018; Firdaus et al., 2020), regional (Matthews et al., 1997; Li et al., 2017; van Oort & Zwart, 2018) and global levels (Olszyk et al., 1999; Lobell & Gourdji, 2012). The primary tools for assessing the effects of climate change on crop yield are crop simulation and statistical models (Shi et al., 2013). These models integrate scientific principles from agronomy, agrometeorology, physiology, and soil science to simulate the complex interactions between rice crops and their environments (Chavas et al., 2009; Shabbir et al., 2020; Solaymani, 2023). On the other hand, statistical models for estimating the impact of climate change on rice yields which involve using quantitative methods to analyze historical data (Trinh, 2018; Rayamajhee et al., 2021; Tan et al., 2021). These models employ techniques such as regression analysis or other machine learning algorithms to identify patterns and correlations between climate variables and crop production (Elbasi et al., 2023). Unlike mechanistic crop simulation models, statistical models do not simulate the underlying physiological processes but focus on empirical relationships within the data. They provide valuable insights into how climatic factors influence crop yields, aiding in the assessment of potential impacts under changing climatic conditions (Lobell & Burke, 2010).

According to Wu et al. (2021), previous studies indicated that statistical models exhibit strong explanatory capabilities and surpass simulation models in accurately assessing data at specific spatial scales. Additionally, the results generated by crop simulation models are sensitive to factors such as soil conditions, weather, and management indices (Shi et al., 2013), whereas studies lack reliable data on soil and management, offering 'best-guess' estimates with limited information on uncertainties from model choices (Schlenker & Lobell, 2010). In addition, climate change has gradually unfolded, and its impact is not immediately apparent. A model must be applied over an extended period of time to capture and understand these effects. Hence, panel data analysis enhances the efficiency and consistency in estimating parameters, particularly when dealing with smaller sample sizes, leading to more robust and reliable results (Baltagi, 2008; Hsiao, 2014).

Nevertheless, conventional panel models, including pooled Ordinary Least Squares (OLS), fixed effects, and random effects models are influenced by strict assumptions, such as the absence of group-wise heteroscedasticity, and autocorrelation within panels of the stochastic disturbance term (Wu et al., 2021). Violating these assumptions can result in biased and inefficient parameter estimates (Wooldridge, 2010). Thus, it is important to apply a model that overcomes these limitations described above (Wu et al., 2021). Internationally, several studies have used the FGLS model to investigate the impacts of climate change (Ali et al., 2017; Kassaye et al., 2021; Wu et al., 2021; Massagony et al., 2023).

3. Materials and methods

3.1. Study area

To analyze the impact of climate change on rice yield in Central Coast of Vietnam, we utilized a panel dataset of the 9 district-level units in Thua Thien Hue Province throughout 1996 to 2021. We chose to

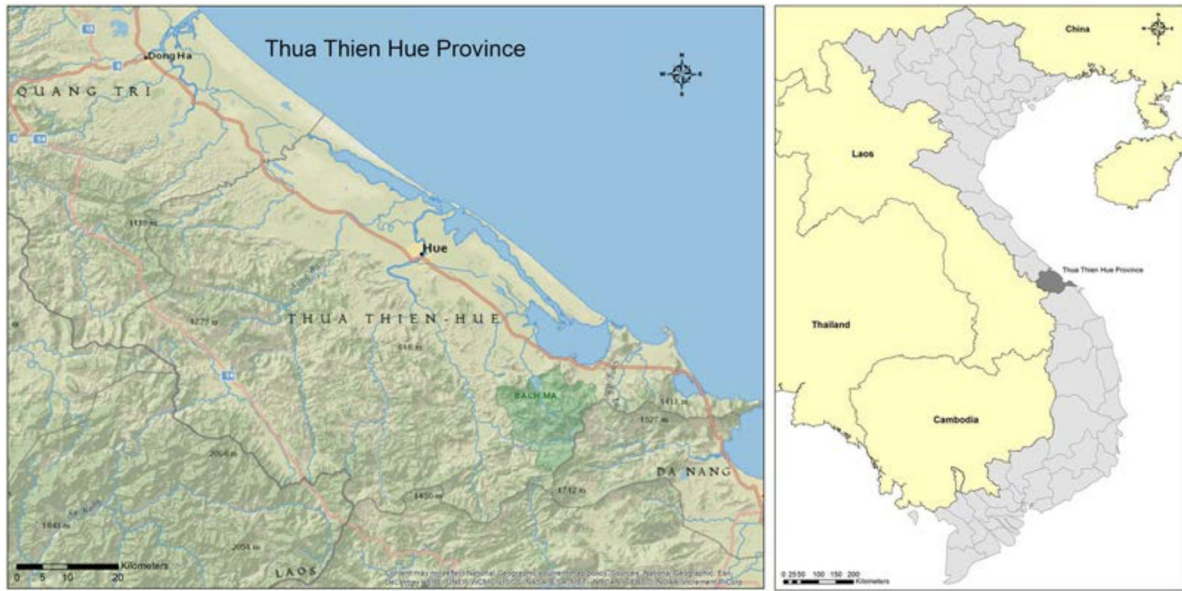


Figure 1. Map of the study area. Source: Wolf et al. (2021).

study in Thua Thien Hue Province because it is one of Vietnam's most climate-vulnerable areas and is often affected by natural disasters such as drought, typhoons, and flooding (Phuong et al., 2018; UNDP, 2018).

As shown in Figure 1, Thua Thien Hue Province is located in the Central Coast region, covering about 5025 km². It borders Quang Tri Province to the north and Da Nang City to the south, shares a 81 km boundary with Laos to the west, and has a 120 km coastline to the east. The province's territory extends in a northwest-southeast direction, with the longest section reaching 120 km along the coast and the shortest, 44 km, in the west. Horizontally, it spans a northeast-southwest direction, with the widest part measuring 65 km and the narrowest, in the southernmost area, approximately 2 to 3 km (TTHPPC, 2024).

3.2. Data collection

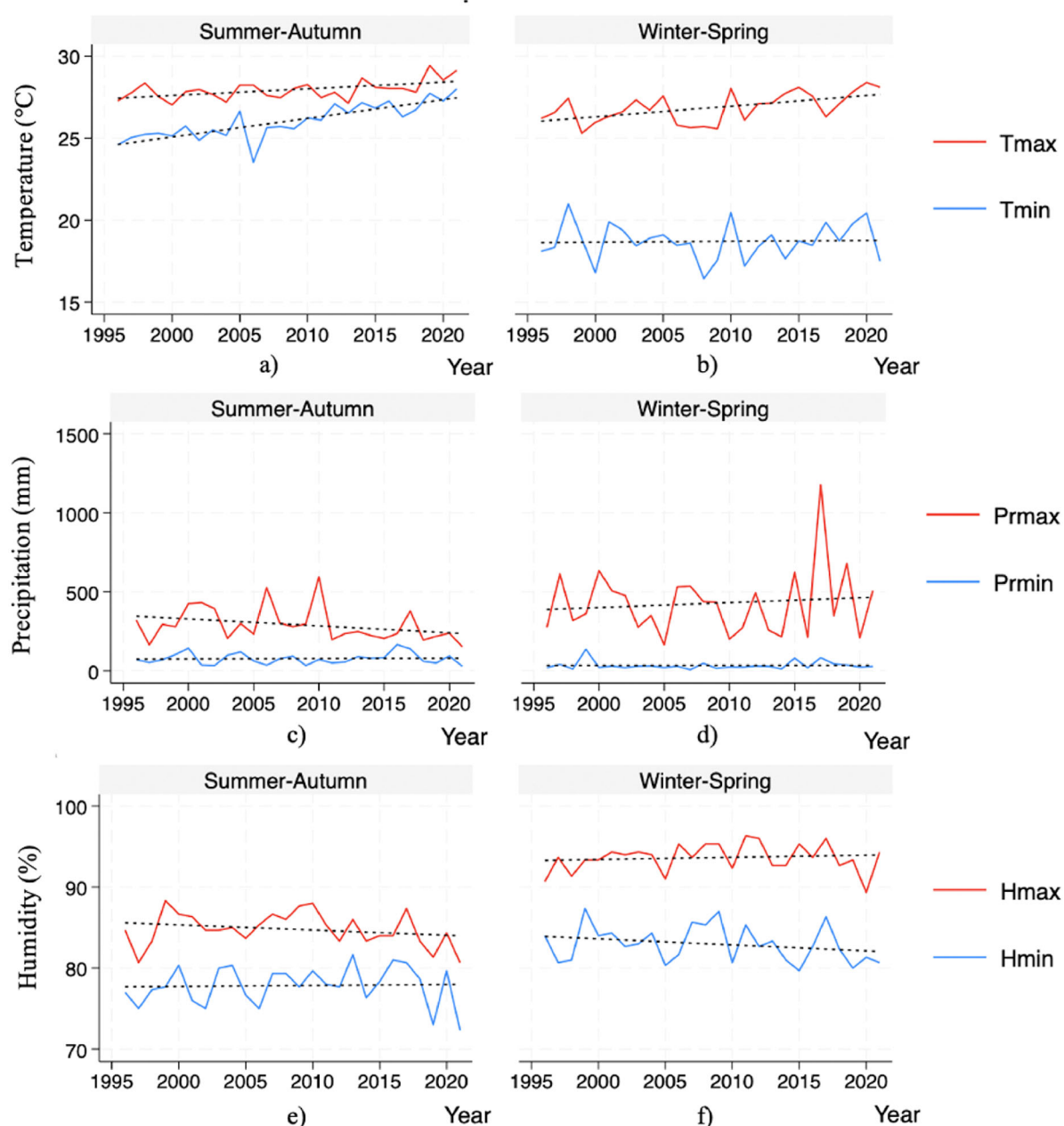
This study used the entire secondary dataset collected from various issues of the Thua Thien Hue Statistical Yearbook, which is published annually from 1996 to 2021 by Thua Thien Hue Statistical Office to reflect the local social, economic, and climatic situations. The data on rice yield were collected for both the winter-spring and summer-autumn seasons from the nine district-level units of the province represented three types of areas: coastal plains, midlands, and highlands. The monthly climatic data were provided by the three-land based meteorological stations from Center for Hydrometeorological Forecasting, located in three areas in Thua Thien Hue Province. The monthly data on meteorological variables, such as temperature and relative humidity, were the averages of daily temperatures and daily relative humidity within each month. The monthly data on precipitation were the total precipitation of all days in the month. The daily data, collected using measurement methods, techniques, and precise equipment, are aggregated into representative average monthly data by meteorological experts and officially published by the Thua Thien Hue Statistics Office, ensuring a certain level of reliability in the study. Furthermore, the long-term research period is designed to offer a comprehensive view of climate change impacts, so minor errors, if present, are considered acceptable.

Besides, minimum and maximum climatic variables used in this study are crucial for understanding the impact of climate change on rice production. Extremes in weather conditions often contribute to variations in rice production and may exert a greater influence on yields (Saud et al., 2022). Additionally, different crops have distinct optimal minimum and maximum climatic conditions, such as temperature and rainfall (Kumar et al., 2021). Therefore, understanding these impacts is necessary for establishing an early warning and forecasting system for extreme weather events (Saud et al., 2022).

Table 1. Descriptive statistics of variables used in the winter–spring season model and summer–autumn season model.

Variable	Definition	Mean	Std.Dev	Minimum	Maximum
<i>Winter–spring</i>					
RY	Rice yield (ton/ha)	5.22	0.92	2.87	7.79
Tmin	Minimum temperature (°C)	19.27	1.46	15.1	21.8
Tmax	Maximum temperature (°C)	27.67	1.44	23.1	29.6
Prmin	Minimum precipitation (mm)	30.62	29.11	1.6	161.1
Prmax	Maximum precipitation (mm)	428.56	248.67	24.4	1218.8
Hmin	Minimum relative humidity (%)	82.37	3.20	75	89
Hmax	Maximum relative humidity (%)	93.51	1.99	87	98
<i>Summer–autumn</i>					
RY	Rice yield (ton/ha)	4.81	0.98	2.03	6.49
Tmin	Minimum temperature (°C)	26.90	1.58	20.2	29.4
Tmax	Maximum temperature (°C)	28.84	1.28	24.7	31.1
Prmin	Minimum precipitation (mm)	54.18	48.50	1.7	217.8
Prmax	Maximum precipitation (mm)	257.37	136.14	52.6	650
Hmin	Minimum relative humidity (%)	77.05	3.04	71	84
Hmax	Maximum relative humidity (%)	83.93	2.81	76	91

Source: Authors' estimation results.

**Figure 2.** The variations in climatic factors affecting rice yield from 1996 to 2021 in Thua Thien Hue Province. Source: Authors' calculation results.

The dataset was collected annually in accordance with the summer–autumn and winter–spring seasons and was compiled over the complete a 26-year period. The data for the winter–spring model were obtained over a 6-month period, spanning from December to May of the subsequent year. The data for the summer–autumn model were acquired over a 4-month period, ranging from May to August. The total dataset was complete, and no missing data were imputed in this study. Finally, a panel dataset of 234 observations for each season model was used in this study, as shown in Table 1.

As demonstrated in Table 1, the minimum and maximum relative humidity indices in the winter–spring season are 82.37 and 93.51, respectively, surpassing those in the summer–autumn season, which stand at 77.05 and 83.93, respectively. While the minimum precipitation in the summer–autumn season (54.18 mm) exceeded that in the winter–spring season (30.62 mm), the maximum precipitation in the winter–spring season (428.56 mm) surpassed the minimum precipitation in the summer–autumn season (257.37 mm). Furthermore, the minimum and maximum temperature indices in the winter–spring season are 19.27 °C and 27.67 °C, respectively, both lower than those in the summer–autumn season, 26.9 °C and 28.84 °C, respectively.

Figure 2 illustrates the trends of climatic factors from 1996 to 2021 in the Central Coast of Vietnam, with the dotted lines indicating the trends of these factors. As shown in Figure 1, there were upward trends in the maximum temperature in both seasons. Over the 26-year period, the maximum temperature increased by 1.8 °C in the summer–autumn season and 1.9 °C in the winter–spring season. During the summer–autumn season, declines were observed in both maximum precipitation and maximum relative humidity, whereas in the winter–spring season, both climate indicators showed increasing trends. The minimum temperature, precipitation, and relative humidity exhibited fluctuations across most seasons, except for the upward trend of minimum temperature in the summer–autumn season by 3.4 °C. Regarding precipitation, the maximum precipitation index with the greatest fluctuations was observed in 2005–2010 in the summer–autumn season, and in 2015–2020 in the winter–spring season. In fact, during the aforementioned periods, the province experienced extreme weather events, especially in 2009/2010 and 2016/2017, with unusually high rainfall of up to 1176.3 mm (2017), leading to historic floods that greatly affected rice production and the livelihoods of farming households.

3.3. Model specification

Based on the literature review, the variables were used in the models including temperature, precipitation, and humidity (Ali et al., 2017; Kumar et al., 2021; Massagony et al., 2023; Tan et al., 2021; Li, 2023). The general form reflecting the relationship between rice yield and climatic factors in this study is written as:

$$RY_{it} = f(Tmin_{it}, Tmax_{it}, Prmin_{it}, Prmax_{it}, Hmin_{it}, Hmax_{it}) \quad (1)$$

where RY denotes the dependent variable, rice yield, in District i at time t ; $Tmin$ denotes minimum temperature; $Tmax$ denotes maximum temperature; $Prmin$ denotes minimum precipitation; $Prmax$ denotes maximum precipitation, $Hmin$ denotes minimum relative humidity; $Hmax$ denotes maximum relative humidity. i represents the district and t represents time. Eq. (1) is transformed into an econometric model in the logarithmic form denoted by Eq. (2), as:

$$\ln RY_{it} = \beta_0 + \beta_1 \ln Tmin_{it} + \beta_2 \ln Tmax_{it} + \beta_3 \ln Prmin_{it} + \beta_4 \ln Prmax_{it} + \beta_5 \ln Hmin_{it} + \beta_6 \ln Hmax_{it} + \mu_{it} \quad (2)$$

where β_0 represents the constant term; while β_1 , β_2 , β_3 , β_4 , β_5 , and β_6 stand for the coefficients associated with explanatory variables; and μ_{it} signifies the error term.

3.4. Econometric methods

For empirical analysis using panel data, two commonly used models are the fixed effects model (FE) and random effects model (RE). However, it is necessary to conduct a robustness check of these models to validate the results derived from the appropriate model (Wu et al., 2021). The findings show that the results derived from these two traditional models cannot address the issues of group-wise heteroscedasticity or

autocorrelation within panels. According to Wooldridge (2010), effectively addressing extensive datasets and challenges related to heteroscedasticity and autocorrelation can be achieved by employing the Feasible Generalized Least Squares (FGLS) method. Considerable focus has been directed towards FGLS in recent years, with several studies employing this method to examine the impact of climate change on agricultural output (Reed & Ye, 2011; Ali et al., 2017; Kumar et al., 2021; Massagony et al., 2023).

Specifically, FGLS is particularly advantageous, producing efficient and consistent estimates of standard errors provided that the panel time dimension (T) is greater than the cross-sectional dimension (N) (Beck & Katz, 1995; Naveen et al., 2021). This condition is satisfied when $N < T$, where N represents the number of cross-sectional units (districts in our case) and T is the time period. In our study with nine districts, the cross-sectional dimension (N) was less than the time period ($T = 26$), confirming the feasibility of the FGLS method.

Therefore, we utilized the feasible generalized least square (FGLS) method in this study. Following Kumar et al. (2021), the general model suggested by Parks (1967) can be expressed as follows:

$$\hat{\beta}_{FGLS} = (X' \hat{\Omega}^{-1} X)^{-1} X' \hat{\Omega}^{-1} y \quad (3)$$

$$Var(\hat{\beta}_{FGLS}) = (X' \hat{\Omega}^{-1} X)^{-1} \quad (4)$$

where $\hat{\Omega}$ is the assumption of autocorrelation and heteroscedasticity, $\hat{\beta}_{FGLS}$ denotes the FGLS estimator of β , y denotes the dependent variables, X denotes the vector of independent variables, and X' denotes the transpose of X .

3.5. Diagnostic tests

Conducting diagnostic tests is crucial to ensure the robustness of the model. The primary tests conducted in this study were as follows:

To determine whether to employ fixed or random effects models, researchers frequently utilize the Hausman test proposed by Hausman in 1978. Nonetheless, it is important to recognize that the Hausman test may not always offer a conclusive decision, as its validity is contingent upon stringent conditions (Buckley et al., 2013). Therefore, we employed a Hausman-like alternative test, known as xtoverid, which presents the Sargan–Hansen test of overidentifying restrictions for a panel data estimation statistic (Schaffer & Stillman, 2016). The null hypothesis states that there is no systematic difference in the coefficients.

To ensure the robustness of the applied panel regression, the Wooldridge's (2010) test was employed to detect autocorrelation. This is necessary because autocorrelation can result in biased standard errors and a reduction in the efficiency of the parameter estimates (Hamilton, 1994). The null hypothesis of the Wooldridge test is that there is no first-order autocorrelation.

The Modified Wald test, as proposed by Baum (2000), is a statistical test used to assess the presence of panel groupwise heteroscedasticity in the fixed-effect regression model. The null hypothesis indicates panel group-wise homoscedasticity and the alternative hypothesis signifies the existence of group-wise heteroscedasticity within the model.

In light of the aforementioned validation, the feasible generalized least squares (FGLS) model was employed to address the autocorrelation and groupwise heteroscedasticity issues of the models.

4. Results and discussions

4.1. Correlation analysis

Tables 2 and 3 show the pairwise correlation matrices between variables used in the models for the summer–autumn and winter–spring seasons, respectively. The primary method for detecting multicollinearity is through a pairwise correlation analysis using a correlation matrix. The results highlight the nonexistence of a high correlation between the variables, effectively mitigating concerns regarding multicollinearity within the dataset. Commonly accepted thresholds, such as 0.8 and 0.9, are employed to identify significant bivariate correlations, as they indicate strong linear associations or a high degree of

Table 2. Correlation matrix of summer–autumn season.

	lnRY	lnTmin	lnTmax	lnPrmin	lnPrmax	lnHmin	lnHmax
lnRY	1.0000						
lnTmin	0.6349	1.0000					
lnTmax	0.4640	0.7899	1.0000				
lnPrmin	−0.2439	−0.3599	−0.5460	1.0000			
lnPrmax	−0.3452	−0.4707	−0.3374	0.4533	1.0000		
lnHmin	−0.0895	−0.2011	−0.4562	0.7648	0.2923	1.0000	
lnHmax	−0.2245	−0.5225	−0.5341	0.4473	0.5850	0.4925	1.0000

Source: Author's estimation results.

Table 3. Correlation matrix of winter–spring season.

	lnRY	lnTmin	lnTmax	lnPrmin	lnPrmax	lnHmin	lnHmax
lnRY	1.0000						
lnTmin	0.0798	1.0000					
lnTmax	0.4376	0.6378	1.0000				
lnPrmin	−0.0409	0.0077	−0.1622	1.0000			
lnPrmax	0.1530	−0.0990	−0.1558	0.0774	1.0000		
lnHmin	−0.2122	−0.3481	−0.7075	0.1108	0.1914	1.0000	
lnHmax	0.1724	−0.3327	−0.3283	0.1368	0.4562	0.3460	1.0000

Source: Authors' estimation results.

correlation between two regressors (Mason & Perreault, 1991; Chan et al., 2022). Since the correlation coefficients between pairs of variables are less than 0.8, there is an absence of multicollinearity among the independent variables. In addition, a Variance Inflation Factor (VIF) test for multicollinearity was conducted to eliminate any uncertainty regarding potential multicollinearity. Variance Inflation Factor is described as a measure that quantifies the extent to which the variance of a regression coefficient is increased due to the linear association between the predictor and other variables, compared to the variance if it were uncorrelated (Chatterjee & Hadi, 2006). A VIF value below 10 is generally considered acceptable because higher values may indicate that multicollinearity is causing poor estimation of the associated regression coefficients (Chatterjee & Hadi, 2006; Montgomery et al., 2012). The resulting mean VIFs of 2.99 in the summer–autumn and 1.85 in the winter–spring models were significantly lower than 10, indicating that multicollinearity was unlikely to be an issue in this case.

4.2. Diagnostic tests

In our initial investigation, we employed panel data models, including both fixed effects (FE) and random effects (RE). Table 4 presents the results of the panel regression. Variables Hmin, Hmax, Prmax, Tmin and Tmax were statistically significant in the FE regression (summer–autumn season), whereas Hmax, Prmax, and Tmin variables were statistically significant in the RE regression (summer–autumn season). In the winter–spring season, Hmin, Hmax, Prmax, Tmin and Tmax were statistically significant in both FE and RE regressions.

Upon estimating the FE and RE models, we conducted a Sargan–Hansen test. As shown in Table 4, the p -value of 0.000 was less than 0.05, leading to the rejection of the null hypothesis at the 5% level of significance. This indicates that the fixed effects regression model was more appropriate for the research Summer–Autumn dataset than the random effects regression model. In addition, with a p -value of 0.000 lower than 0.05, the null hypothesis was rejected at the 5% level of significance, indicating that the fixed effects model was appropriate for the winter–spring model.

The outcomes of the diagnostic tests are shown in Table 5. The Modified Wald test was conducted to assess the issue of group-wise heteroscedasticity in the summer–autumn season model using fixed-effects regression. With a p -value of 0.000, the model was statistically significant, which indicates that the null hypothesis was rejected at the 5% level of significance, meaning that group-wise heteroscedasticity existed in the model. Similarly, the test was conducted to check the issue of group-wise heteroscedasticity in the winter–spring season model using fixed effects regression. The model had p -value of 0.0000, which was less than 0.05, indicating that the null hypothesis of homoscedasticity was rejected at

Table 4. Panel regression results for summer–autumn and winter–spring seasons.

Variable	Summer–autumn		Winter–spring	
	Fixed effect Coefficient	Random effect Coefficient	Fixed effect Coefficient	Random effect Coefficient
lnTmin	1.9913*** (0.3204)	2.3946*** (0.3288)	−0.7362*** (0.1610)	−0.7589*** (0.1635)
lnTmax	3.4800*** (0.7917)	0.6542 (0.5665)	4.3170*** (0.4678)	3.6641*** (0.3977)
lnPrmin	0.0023 (0.0172)	−0.0046 (0.0179)	0.01435 (0.0104)	0.0127 (0.0105)
lnPrmax	−0.0640** (0.0263)	−0.0510* (0.0274)	0.0394** (0.0164)	0.0372** (0.0167)
lnHmin	1.3924*** (0.4841)	0.4539 (0.4754)	1.4524*** (0.4057)	1.1258*** (0.3843)
lnHmax	0.9370** (0.4621)	1.1392** (0.4785)	2.0992*** (0.5322)	2.0205*** (0.5387)
Constant	−26.5592*** (3.784)	−15.2545*** (3.0492)	−26.7221*** (3.8858)	−22.6733*** (3.5362)
R ²	0.3626	0.4236	0.3559	0.3680
Sargan-Hansen Statistic		36.583		110.866
P-value		0.000		0.000

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The standard errors are shown in parentheses.

Source: Author's estimation results.

Table 5. Results of diagnostic tests.

Season	Test	Statistics	
Summer–Autumn	Modified Wald Test	Chi2(9)	140.10
		Prob > chi2	0.0000
	Wooldridge Test	F(1,8)	5.053
		Prob > F	0.0547
Winter–Spring	Modified Wald Test	Chi2(9)	218.29
		Prob > Chibar2	0.0000
	Wooldridge Test	F(1,8)	32.819
		Prob > F	0.0004

Source: Authors' estimation results.

the 5% level of significance. This result implies that there was an issue of group-wise heteroscedasticity in the model.

Subsequently, Wooldridge test was performed to check for the presence of autocorrelation in the models. The summer–autumn season model had the test results of $F(1,8) = 5.053$ and $\text{Prob} > F = 0.0547$, which was greater than 0.05. This was not statistically significant, and the null hypothesis was accepted at the 5% level of significance, implying that there was no autocorrelation in the model. In contrast, the winter–spring season model had the test results of $F(1,8) = 32.819$ and $\text{Prob} > F = 0.0004$ which was smaller than 0.05. This indicated that the null hypothesis was rejected at the 5% level of significance; hence, the model suffered the issue of autocorrelation.

The diagnostic tests revealed that the summer–autumn season model employing FE regression exhibited group-wise heteroscedasticity, whereas the winter–spring season model utilizing FE regression encountered both group-wise heteroscedasticity and autocorrelation issues. Therefore, to ensure reliable and effective estimates, FGLS was used in this study to mitigate the limitations observed in the aforementioned panel models.

4.3. FGLS estimation results

Table 6 illustrates the estimation results examining the impacts of climate change on rice yields in Thua Thien Hue Province, employing the feasible generalized least squares (FGLS) model analysis. The findings showed that in the winter–spring season, the estimated coefficient of $Tmax$ is positive and statistically significant at the 1% level. The value of the coefficient of $Tmax$ reveals that the winter–spring rice yield is expected to increase by 1.6581%, with every 1% increase in $Tmax$. In contrast, the estimated coefficient of $Tmax$ during the summer–autumn season is negative and statistically significant at the 5% level. Specifically, for every 1% rise in $Tmax$, the summer–autumn rice yield decreased by 1.0047%.

Table 6. Results of FGLS estimation.

Variable	Winter–spring		Summer–autumn	
	Coefficient	Standard error	Coefficient	Standard error
lnTmin	−0.3035***	0.0847	3.3186***	0.3407
lnTmax	1.6581***	0.2955	−1.0047**	0.4383
lnPrmin	−0.0022	0.0052	−0.0093	0.0165
lnPrmax	0.0122	0.0092	−0.0386*	0.0230
lnHmin	0.8557***	0.2271	0.1501	0.4244
lnHmax	1.2912***	0.3203	1.4363***	0.4068
Constant	−12.6592***	2.5077	−12.7490***	2.4154
Wald chi2(6)	64.17		270.97	
Prob > chi2	0.000		0.000	

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The standard errors are shown in parentheses.

Source: Authors' estimation results.

In addition, the estimated coefficient of *Tmin* in the winter–spring season is negative, whereas it is positive in the summer–autumn season, both of which are statistically significant at the 1% level. The values of the coefficients reveal that a 1% increase in *Tmin* decreases rice yield by 0.3035% in the winter–spring season. In contrast, for every 1% increase in *Tmin*, the rice yield in summer–autumn season is estimated to increase by 3.3186%.

Regarding precipitation, the estimated coefficient of *Prmax* in the summer–autumn season is negative and statistically significant at the 10% level. The value of *Prmax* justifies that a 1% increase in *Prmax* decreases in the summer–autumn rice yield by 0.0386%.

For humidity, in the spring–winter season, the estimated coefficient of *Hmin* is positive and statistically significant at the 1% level. The coefficient of *Hmin* shows that spring–winter rice yield increases by 0.8557%, with a 1% increase in *Hmin*. This indicates that the minimum humidity has a positive impact on rice yield during the spring–winter season. Moreover, the estimated coefficients of *Hmax* in both models are positive and statistically significant at the 1% level. Specifically, a 1% rise in *Hmax* would increase the winter–spring and summer–autumn rice yields by 1.2912% and 1.4363%, respectively.

4.4. Discussion

Over the 26-year period, the climate change factors exhibited annual variations (see Figure 2). The average annual maximum temperature increased by 0.069 °C during the summer–autumn season and by 0.073 °C during the winter–spring season. The average annual minimum temperature rose by 0.131 °C in the summer–autumn season, while it decreased by 0.023 °C in the winter–spring season. Additionally, the annual maximum precipitation decreased by 6.5 mm during the summer–autumn season. For relative humidity, the average annual maximum decreased by 0.154% during the summer–autumn season and increased by 0.138% during the winter–spring season. Conversely, the average annual minimum relative humidity declined by 0.127% during the winter–spring season.

Based on the findings of this study in Table 6, the maximum temperature positively affects rice yield in the winter–spring season. This is likely due to the fact that in the winter–spring crop, the highest temperature remains relatively low. Consequently, warmer temperatures are expected to positively influence on the growth and development of rice plants. In fact, the rice yield increased from 5.54 tonnes to 5.62 tonnes over the 2009–2010 period (TTHSO, 2010). This finding supports the empirical results found in previous studies of Ali et al. (2017) and Li (2023). By contrast, the maximum temperature has a negative impact on the rice yield during the summer–autumn season. This is likely due to the fact that the Summer–Autumn rice crop is the hottest season of the year, causing the increase in maximum temperature to adversely affect rice growth, as evidenced by a decline in rice yield from 6.07 tonnes to 5.75 tonnes during the 2018–2019 period (TTHSO, 2019). The result is in line with those of previous studies (Shabbir et al. 2020; Massagony et al. 2023; Solaymani, 2023).

While the minimum temperature has a negative impact on rice yield in the winter–spring season, it positively affects rice yield in the summer–autumn season. This is consistent with the typical weather conditions of the winter–spring season, which are characterized by low temperatures; hence, warmer weather during this period would consequently have a detrimental effect on rice growth. Indeed, this is

reflected by the reduction in the rice yield from 6.62 tonnes to 5.9 tonnes over the 2019–2020 period (TTHSO, 2019). The finding is consistent with that of Lobell and Gourdji (2012), Ali et al. (2017), and Massagony et al. (2023). Conversely, the summer–autumn season is typically characterized by warm weather, which makes an increase in minimum temperature conducive to rice growth and improved yield. It is consistent with the findings of Tan et al. (2021) and Li (2023).

In terms of precipitation, the maximum precipitation has a negative impact on rice yield during the summer–autumn season. This was likely due to the frequent occurrence of heavy rains, storms and floods during the middle and end of the season (from August to September), coinciding with the rice flowering and ripening period, thereby resulting in drowning or damage to rice plants, ultimately reducing yields. This is indicated in the decline in rice yield from 5.33 tonnes to 5.07 tonnes over the period of 2009–2010 (TTHSO, 2010). The result is consistent with that of Zhao et al. (2022), Tan et al. (2021), and Massagony et al. (2023).

In relation to humidity, the maximum relative humidity also positively impacts on rice yield in both seasons. This can be explained by the fact that maintaining relative humidity ensures the presence of adequate moisture in the air, thereby alleviating water stress on rice plants, particularly in regions susceptible to drought caused by escalating temperatures. Consequently, an increase in humidity levels may enhance rice yields. For instance, this is evidenced by the increase in winter–spring rice yield from 6.07 tonnes to 6.24 tonnes during the 2016–2017 period (TTHSO, 2017). It is consistent with the findings of Zhang et al. (2017) and Massagony et al. (2021). Specifically, Zhang et al. (2017) and Massagony et al. (2023) highlighted the significance of additional climatic factors, such as humidity, for crop growth, because neglecting this variable could lead to biased predictions of the impacts of climate change on crop yields.

Overall, this study showed that the impact of climate change on rice productivity is complex and multifaceted. Notably, while climate change can have detrimental effects on rice yields, it may also exert positive influences in certain situations, depending on the specific seasonal rice crops under consideration. The study's significant findings indicate that an increase in maximum temperature and minimum temperature is beneficial to rice yields during the winter–spring and summer–autumn seasons, respectively. This result contrasts with the findings of a previous study conducted in Central Vietnam by Chung et al. (2015). Furthermore, the increase in both maximum and minimum relative humidity has been identified as having a positive effect on rice yields. This finding underscores the critical importance of humidity in rice production, which is rarely mentioned in previous studies conducted in the study area (Chung et al., 2015; Trinh, 2018; Nguyen & Scrimgeour, 2022).

5. Conclusion and policy implications

Climate change, with its profound impact on agricultural production, has emerged as a global concern, largely due to the critical importance of food security. In response to this growing issue, the study examines the impacts of seasonal climate change on rice productivity in the Central Coast of Vietnam. In general, the results of this study revealed the distinct impacts of climatic variation on rice yield across different seasons. Furthermore, the study highlighted significant findings that increases in maximum and minimum temperatures, are not only detrimental but also beneficial for rice yields, considering different crop seasons. It also provided evidence emphasizing the crucial role of humidity in rice production.

Specifically, during the winter–spring season, it was observed that the minimum temperature negatively impacts rice yield, while both minimum and maximum relative humidity, along with the maximum temperature, were found to exert a positive influence on rice yield during this period. Conversely, in the summer–autumn season, the maximum relative humidity and minimum temperature positively affected rice yield. However, elevated levels of maximum precipitation and maximum temperature during this season were identified as detrimental factors that negatively impacted rice yield.

These findings underscore the significance of recognizing seasonal variations in weather dynamics when assessing the rice cultivation productivity, thereby emphasizing the need for tailored agricultural strategies based on prevailing climatic conditions. The study recommends that rice producers enhance the resilience of rice production to climate change, which necessitates the improvement of water

supply and drainage systems in low-lying areas and regions adjacent to the lagoon. Second, priority should be given to ensuring adequate moisture levels for the crops, particularly during the dry season. Thirdly, disseminating adaptive rain and storm warning information to communities and introducing drought-resistant and flood-tolerant rice varieties represent effective measures to promote the increased adaptability of rice production to climate change.

This study offers valuable insights into the impact of climate indicators on rice productivity. However, certain limitations, such as data constraints, should be addressed in future research. Although the study highlights the seasonal impact of climate change on rice crops, the available data did not allow for a more intensive analysis of the effects on each growth stage of the rice plant. Future studies that integrate specific farming techniques may help overcome this limitation, leading to the development of a more detailed climatic warning system for rice farmers and policymakers.

Authors contributions

Conceptualization, P.T.M.N., P.T.H., and H.X.P.; methodology, P.T.M.N., P.T.H.; validation, P.T.M.N., P.T.H., and H.X.P.; formal analysis, P.T.M.N., P.T.H.; writing—original draft preparation, P.T.M.N.; writing—review and editing, P.T.M.N., P.T.H.; supervision, P.T.M.N., P.T.H., and H.X.P. All authors have read and agreed to the published version of the manuscript.

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Data availability statement

The dataset is obtained from the Thua Thien Hue Statistical Yearbook which is published annually from 1996 to 2021 by Thua Thien Hue Statistical Office. The dataset and materials supporting the results or analysis presented in this study are available from the authors upon reasonable request.

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